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INTRODUCTION

"The future of grocery shopping is multi-channel" (Joanne Denney-Finch, chief executive, IGD 2009). Multi-channel grocery shoppers, who regularly visit both online and offline grocery stores, are a rapidly growing segment that dramatically changes the 'currently saturated' grocery market (IGD 2011). The upcoming trend of grocery shoppers using multiple channels challenges retailers to think about how to construct their operation models and how to implement marketing mix strategies (Retail Systems Research 2013). Multi-channel shoppers are not only exposed to marketing actions of the online as well as the offline channel, they also seem to seize the opportunity to take advantage of the special offers available across these different channels. A survey conducted by IGD (2011), for instance, has shown that 49% of respondents say they use several channels to take advantage of promotions and 37% of respondents say they want to save money by using multiple channels. An important consideration for multi-channel retailers is thus which promotion strategy to adopt across channels.

In this research, we focus on retailers that offer a *differentiated* promotion program across their *online and offline channel*.[1] The practice of offering different promotions across the online and offline channel has been widely adopted by retailers, often for pragmatic reasons (e.g.,

[1] We define sales promotions as temporary price discounts (see Data section). We focus on consumer reactions towards these sales promotions, and hence do distinguish between promotions that are initiated by either the manufacturer or retailer. Most of these promotions are accompanied by offline feature and display advertising (cf. Blattberg and Neslin 1989) or online advertising in the form of banners and shelf tags. Unfortunately we do not have sufficiently detailed data to distinguish between these sales promotion forms, which tend to be highly correlated anyways because they are often used together (cf. Blattberg and Neslin 1989).

because each channel has its own account manager who is responsible for day-to-day operations like promotions; Avery et al. 2012). For instance, two large European multi-channel grocery retailers, Ahold and Delhaize, have in a given week a different set of promotions available in their online and offline stores. There are pros and cons associated with the adoption of such a differentiated promotion strategy. On the one hand, as a result of the differences in shopping environment, consumers' sensitivity and response to promotions may differ across channels (Neslin et al. 2006; Chu et al. 2010). A differentiated promotion strategy that exploits these differences in promotion sensitivity may lead to higher effectiveness and profitability (Wolk and Ebling 2011). On the other hand, most online grocery shoppers are multi-channel shoppers, implying that they do not belong to a separate online and offline shopper segment (Chu et al. 2008) and that following a differentiated strategy may reduce the consistency in chain image and appeal (Shankar et al. 2011). In addition, when multi-channel shoppers are exposed to different promotions in the online and offline channel, they may adjust their behavior to take maximum advantage of promotion opportunities, leading to shifts in category sales from one channel to the other, rather than an overall boost in category sales for the chain as a whole. Finally, multi-channel shoppers may encounter a larger number of promoted items in a given time period and may therefore more easily 'get used' to promotions being offered. This increased promotion exposure can reduce their overall promotion responsiveness (Foekens et al. 1999; Kalyanaram and Winer 1995; Kopalle et al. 1999).

Because a differentiated promotion strategy can have positive as well as negative outcomes, it is important to investigate and understand how channel differences in promotion strategy can affect buying behavior in both channels. The previous discussion demonstrates that this problem is far more complex than getting insights into the difference in promotion responsiveness across both channels, and that the impact of potential cross-channel promotion effects should also be taken into account. The major objective of this research is to investigate these cross-channel promotion effects, where we take the point of view of a grocery retail chain that differentiates promotion actions across its online and offline channel. This multi-channel single-chain context allows us to concentrate on cross-channel promotion effects that are caused by pure online and offline channel differences rather than confounding effects of other differences in a multi-chain context (e.g., differences in price/quality positioning, retail store image). Our focus also lies on how promotions change in-store purchase behavior within a category, more particularly, category purchase incidence and quantity decisions across channels, (i.e., primary demand effects) which are the most relevant outcomes from a retailer point of view (Ailawadi et al. 2006; Bell et al. 1999; van Heerde et al. 2003).

Based on prior research on promotion effects in an offline shopping context, we can derive three major issues that need to be examined to get a better insight into the nature and importance of cross-channel promotion effects. First, prior research provided evidence of strong cross-competitive effects, at the store choice as well as the category level, with category promotions in one store leading to pre-emption of category purchases in another regularly visited store (Bucklin and Lattin 1992). Along these lines, we want to investigate whether category promotions in one channel affect category purchase decisions of multi-channel shoppers in the other channel (cross-channel immediate effect). Second, research on the delayed effect of promotions has shown that frequent own and competitive promotion activities in the past can reduce the consumer’s future promotion sensitivity (e.g., Foekens et al. 1999; Kalyanaram and Winer 1995). Our second research objective is to investigate whether similar delayed promotion effects exist across channels, where past category promotions in one channel reduce consumers’ category-specific promotion sensitivity in the other channel (cross-channel delayed effect), increasing the risk of reduced promotion sensitivity. Third, consumers are heterogeneous in responsiveness to marketing actions and prior promotion research has repeatedly demonstrated the importance of controlling for household heterogeneity (Bucklin and Gupta 1992; Bucklin et al. 1998; Bucklin and Lattin 1992; van Heerde and Neslin 2008; Zhang and Krishnamurthi 2004; Zhang and Wedel 2009). Translating this to the multi-channel context, our third research objective is to investigate whether cross-channel immediate and delayed promotion effects have a stronger negative impact on purchase decisions for some types of consumers than for others.

From an academic point of view, this research provides important contributions to the promotion and multi-channel retailing literature. For one, it extends the promotion literature by examining cross-channel promotion effects in a multi-channel context. Previous literature focused on cross-competitive promotion effects on brand or store choice within the offline channel (Ailawadi and Neslin 1998; Bell et al. 1999; Blattberg et al. 1995; Bucklin and Gupta 1992). Studies that examined promotion effects in different channels mainly focused on differences in promotion effectiveness between channels, but did not examine whether promotions in one channel may also affect purchase decisions in the other channel (Chu et al. 2008; Zhang and Wedel 2009). This research also extends the multi-channel shopping literature as it is, to the best of our knowledge, the first to examine the effects of a differentiated promotion strategy across channels, taking into account both cross-channel immediate effects on purchase behavior and cross-channel delayed effects on consumers' promotion sensitivity. From a managerial point of view, our research helps multi-channel retailers to gain insights in the complex trade-off between the pros and cons of a differentiated promotion strategy. This may help them to improve their overall business strategy and to optimize cross-channel synergies through effective promotion planning.

To analyze cross-channel immediate and delayed promotion effects, we estimate a model that captures purchase incidence and quantity decisions in the category, that allows for channel-specific and time-varying promotion effects, and that incorporates a latent class estimation to account for unobserved consumer heterogeneity. We have access to a unique data set from a representative UK household panel from Kantar Worldpanel obtained from AiMark for the period starting July 2006 till December 2007. Our data cover household (online and offline) grocery purchases and allows to deduce online and offline promotion information. We estimate category purchase decision models for two frequently purchased categories, milk and cereals, across the online and offline channel of Tesco, the market leader in the grocery sector in the UK both for the online as well offline channel. The empirical results confirm that sales promotions have strong positive effects on category purchase decisions within the channel, but may also negatively affect category purchase decisions in the other channel. Cross-channel delayed effects, on the other hand, appear to be weak or insignificant, implying that the opportunities for cross-channel promotion differentiation entail a low risk of coming at the cost of reduced promotion sensitivity in the long run. In addition, we find clear evidence that cross-channel promotion effects are heterogeneous and especially come into play for segments with more loyal multi-channel shoppers.

In the next section, we describe the conceptual framework that is used to derive expectations on cross-channel immediate and delayed promotion effects. Next, we describe our modeling approach and the data that were used for the empirical analysis. After an overview and discussion of the estimation results, we conclude with our main findings and an overview of important managerial implications. Finally, we discuss some limitations and extensions for further research.

CONCEPTUAL FRAMEWORK

Based on the insights from previous research on immediate and delayed promotion effects in an offline shopping context (e.g., Ailawadi and Neslin 1998; Bucklin and Gupta 1992; Chiang 1995; Chintagunta 1993; Foekens et al. 1999; Mela et al. 1998; Pauwels et al. 2002; Sun et al. 2003), we develop a conceptual framework describing the expected effects of promotions on category purchase decisions in a multi-channel context. Given that our focus is on quantifying the impact of cross-channel promotions from a retailer's perspective, we focus on primary (incidence/quantity) rather than secondary (brand choice) demand effects (Ailawadi et al. 2006; Bell et al. 1999; van Heerde et al. 2003). In the following discussion, we do not explicitly distinguish between category purchase incidence and quantity decisions, as previous research has demonstrated that there is a similar direction in how promotions affect these decisions (Bell and Hilber 2006; Neslin 2002). We do, however, allow the *magnitude* of the effects to differ in our empirical analyses (see Model section). Figure 1 gives a visual representation of the conceptual framework. We first discuss the *within-channel* immediate and delayed promotion effects, which have already been examined in previous (offline) promotion studies. Next, we discuss the expected *cross-channel* immediate and delayed promotion effects. Lastly, we explore how these cross-channel promotion effects may differ across households.

<Insert Figure 1 about here>

Within-channel immediate effects

Several studies have demonstrated that sales promotions can have a strong *immediate* positive effect on consumers' category purchase decisions in offline stores (Bucklin and Gupta 1992; Gupta 1988). By increasing the attractiveness of promoted items, sales promotions can induce consumers to accelerate their purchases and/or stimulate them to buy larger quantities for future consumption (i.e., positive effects on primary demand: Ailawadi and Neslin 1998; Bell et al. 1999; Bucklin and Gupta 1992; Mace and Neslin 2004; Sun et al. 2003; van Heerde et al. 2000; van Heerde et al. 2003). Similar promotion stimulating effects on purchase decisions have been reported for online promotions (Degeratu et al. 2000; Zhang and Krishnamurthi 2004; Zhang and Wedel 2009). The immediate effect of promotions on category purchase decisions in the offline store environment is shown to be stronger when category level promotions are more attractive, which may depend on the number of category items on promotion, the magnitude of promotional advantages, and the consumers' preference for the promoted items (Nijs et al. 2001; Shankar and Bolton 2004). We expect that this may also hold for the online store environment, and therefore hypothesize that – for both channels – a more attractive promotional offer (i.e., more items on promotion, and/or larger price discounts and/or promotions for more preferred SKUs) increases the likelihood of buying the category as well as the amount that is bought in the current period. Hence,

H_1: A more attractive category promotion offer in a channel has an immediate positive impact on consumers' category purchase decisions in this channel.

Within-channel delayed effects

Previous research on the *delayed* effects of promotions has indicated that frequent exposure to promotions may affect consumers' perceptions of and sensitivity to promotional actions (Krishna et al. 1991). When promotions become endemic, consumers may change their future expectations about the value and frequency of deals, ultimately even leading to a situation where they consider promotional deals as normal (Blattberg et al. 1995). As promotions lose their exceptional appeal, they no longer provide an incentive for consumers to buy earlier and/or more (Mela et al. 1998). As a result, frequent exposure to promotions can make consumers less sensitive to future promotions (Foekens et al. 1999; Kalyanaram and Winer 1995; Kopalle et al. 1999). While this effect has only been examined in an offline store context, we expect the underlying mechanism and effect to hold for the online channel as well. Frequent promotions in an online store can change consumers' future expectations about the perceived value and frequency of promotions in a similar way as has been observed in an offline context. Therefore, we expect that:

H_2: A higher frequency of category sales promotions in previous periods in a particular channel reduces the impact of current period category promotions on current category purchase decisions within the channel.

Cross-channel immediate effects

Prior research has suggested that promotions stimulate switching and trigger a change in purchase decision from the planned or favorite option to the promoted alternative, as the promotion-induced increase in utility can help the promoted alternative to surpass the utility of otherwise chosen options (Blattberg and Neslin 1990; Bucklin et al. 1998; Chiang 1991; Foubert and Gijsbrechts 2007; Gupta 1988; Neslin 2002). Evidence has also been provided for direct and indirect store switching effects triggered by promotions (Ailawadi et al. 2006; Bucklin and Lattin 1992; Kumar and Leone 1988; MacKenzie and Walter 1988). Promotions can not only increase the overall attractiveness of a store and attract customers that would otherwise not have visited the store (direct store switch). They can also influence category allocation patterns of consumers who regularly visit multiple stores, and lead to pre-emption of category purchases in one of the other frequented stores (indirect store switch; Bucklin and Lattin 1992). Given that multi-channel shoppers plan their purchases to take maximum advantage of promotions and other opportunities they encounter when visiting different channels (IGD 2011), we expect similar indirect channel switching effects of promotions in a multi-channel context. Promotions that temporarily increase the relative attractiveness of a category in a specific channel are expected to have a positive effect on category purchase decisions within that channel, resulting in a negative effect on the category purchase decision in the other channel. Hence:

H_3: A more attractive category promotion offer in one channel has an immediate negative impact on consumers' category purchase decisions in the other channel.

Cross-channel delayed effects

Multi-channel shoppers who interchangeably shop in the online and offline channel of the same grocery chain may consciously or unconsciously store information on category sales promotions of both channels in their memory, and use it to form expectations on future promotion activities. Consequently, a high frequency of promotions in one or both channels could lead to the expectation that there will be frequent opportunities in the future to buy the category in promotion. This may reduce the consumers' sensitivity to promotions in both channels, as there is no need to displace future purchases to the current promotion period, which would only lead to an increase in storage costs (Blattberg et al. 1995). Consequently, a high frequency of category sales promotions in the past in one channel may not only reduce consumers' sensitivity to promotions in the same channel, but also reduce consumers' sensitivity to promotions in the other channel. Therefore:

H_4: A higher frequency of category sales promotions in previous periods in a particular channel reduces the impact of current period category promotions on current category purchase decisions in the other channel.

Household differences

Obviously, these cross-channel immediate and delayed effects may differ across households (cf. van Heerde and Neslin 2008). First, they can only affect category purchase behavior of multi-channel shoppers who visit the offline and online store of the same chain (cross-channel effects do not come into play for single-channel shoppers). Second, we expect that the effects will be stronger for customers that are more loyal to the chain, i.e., those that spend a larger share of their purchases at the focal chain. When consumers are less loyal and regularly visit multiple chains (multiple store shoppers; see e.g., Gijsbrechts et al. 2008; Vroegrijk et al. 2013), they may not only shift category purchases across channels, but they may also shift category purchases across chains. Hence, consumers that are less loyal have more opportunities to reduce their category purchases in other chains in response to attractive promotions in the focal chain (resulting in lower cross-channel immediate effects), and may have a lower sensitivity to the promotion frequency in the focal chain (resulting in lower cross-channel delayed effects). As the degree of loyalty can differ across categories (cf. Bell and Lattin

1998), we focus on category-specific loyalty and expect that negative cross-channel immediate and delayed promotion effects will be more pronounced for category loyal customers of the chain.

H_{5a}: The negative cross-channel immediate effect on category purchase decisions will be more pronounced in segments with more multi-channel shoppers.

H_{5b}: The negative cross-channel immediate effect on category purchase decisions will be more pronounced in segments with more category loyal customers of the chain.

H_{5c}: The negative cross-channel delayed effect on category purchase decisions will be more pronounced in segments with more multi-channel shoppers.

H_{5d}: The negative cross-channel delayed effect on category purchase decisions will be more pronounced in segments with more category loyal customers of the chain.

MODEL

To analyze within- and cross-channel promotion effects, we concentrate on consumers' category purchase decisions, given channel and chain choice. Channel choice, i.e., the decision to visit the online or offline channel, and chain choice, i.e., the decision to visit a particular chain, are treated as exogenous decisions. The main reasons for analyzing category purchase decisions for a single multi-channel grocery chain are that we want to focus on mere channel allocation effects at the category level, while keeping the analysis tractable. In line with previous studies on category level promotion effects, we define sub models for (i) the purchase incidence decision, i.e., the decision to make a category purchase in a particular channel of the chain (given channel and chain visit), and (ii) the purchase quantity decision, i.e., the decision on how much volume to buy from the category in the channel of the chain (given purchase incidence). While we expect promotions to affect both decisions in the same direction, the magnitude of effects can differ between both decisions. Both models are estimated simultaneously using maximum likelihood procedures (and Latent Gold software which allows to define latent classes over both models simultaneously; see Vermunt and Magidson 2005). The indices i, t and c refer to the household, purchase occasion[2] and channel respectively (for reasons of parsimony, we leave out the category and segment indices). To distinguish between within- and cross-channel effects, we use the indicator c and $\bar{c}$ to denote the own and competitive channel, and c=1 for the online and c=2 for the offline channel.

The category purchase incidence model explains whether household i makes a category purchase in channel c on purchase occasion t ($b_{it,c}$) and is described by the Probit model below:

$$(1) \qquad b_{it,c} = \begin{cases} 1, & if\ b^*_{it,c} > 0 \\ 0, & otherwise \end{cases},$$

where $b^*_{it,c}$ is a latent variable capturing the attractiveness for household i to make a purchase in the category in channel c on purchase occasion t, modeled by the following linear specification:

$$(2) \qquad b^*_{it,c} = (\alpha_0 + \alpha_1 * onvst_{it} + \alpha_2 * \log(CR_i) + \alpha_3 * \mathrm{MCINV}_{it} + \alpha_4 * \log(INV_{it}) + \alpha_{5c} * loyal_{it,c}) + (\mu_{1c} * promo_{it,c} + \mu_{2c} * promo_{it,\bar{c}}).$$

All the details on the operationalization of the variables can be found in Table 1, and will be explained in the Data section. The expression within first brackets measures the household's baseline category purchase tendency in the absence of promotions. The average tendency to buy in the category (captured by the intercept α_0) is adjusted for possible channel differences using an online channel dummy variable ($onvst_{it}$). The overall tendency to buy the category in the online channel is then equal to $\alpha_0 + \alpha_1$. We expect the online correction parameter α_1 to be positive,

[2] In line with previous studies on purchase category decisions (see van Heerde and Neslin 2008), we model decisions made at a 'purchase occasion' (in our case, periods with a visit to the channel) rather than absolute points in time such as every week, since we treat the visit to the channel as given. Hence, we focus only on weeks where households are in the opportunity to buy the category in a given channel.

given the consumers' tendency to buy larger baskets online (Chintagunta et al. 2012). To get an accurate estimate of household consumption needs and inventory effects, we use the procedure suggested by Bell and Boztuğ (2007). The consumption rate parameter α_2 is expected to be positive: higher consumption needs leading to a stronger tendency to make a purchase in the category. In contrast, the (mean-centered) inventory parameter α_3 is expected to be negative: higher than usual household stocks reducing the need to purchase the category. In this way, we also capture dynamic promotion effects (purchase acceleration and stock-piling effects) and account for past promotion effects on current category purchase decisions (Neslin and Schneider Stone 1996). Bell and Boztuğ (2007) suggest that in addition to the traditional mean-centered inventory variable that controls for heterogeneity across different households, there can also be a positive effect due to inventory estimation bias. To test for this inventory bias, we include a log inventory variable which we expect to be positive (captured by α_4). In addition, we include channel-specific loyalty variables ($loyal_{it,c}$) (cf. Guadagni and Little 2008), which capture a household's habit or preference to purchase a category in a specific channel of a given chain. The related parameters (α_{5c}) are expected to be positive: a higher category-specific loyalty to channel c of the focal chain in the past leading to a higher tendency to repurchase the category in that channel.

<Insert Table 1 about here>

The expression within second brackets captures within- and cross-channel promotion effects ($promo_{it,c}$ and $promo_{it,\bar{c}}$ respectively). The within-channel promotion variables ($promo_{it,c}$) are household- and channel-specific category promotion variables, measured as weighted promotional price reductions offered in the category and channel on a given purchase occasion. These variables are household-specific because (i) we focus on visits to a channel where the household is in the opportunity to buy the category and (ii) use household preferences for specific items (based on the share in category purchases in the initialization period) as weights (see Data section and Table 1 for operationalization details). The parameters are expected to be positive ($\mu_{11} > 0$ and $\mu_{12} > 0$), reflecting that more attractive promotion offers in a channel have an immediate positive impact on consumers' category purchase incidence decisions in that channel (cf. H_1).

The cross-channel promotion variables ($promo_{it,\bar{c}}$) are constructed in the same way, but only taking those purchase occasions into account where household i visited the other channel ($\bar{c}$) within the same week, and thus was exposed to promotions in that channel. The parameters of cross-channel promotion variables are expected to be negative ($\mu_{21} < 0$ and $\mu_{22} < 0$), reflecting that more attractive promotion offers in one channel may have an immediate negative impact on consumers' category purchase incidence decisions in the other channel (cf. H_3).

To incorporate delayed promotion effects, we use a model with varying parameters (Foekens et al. 1999; Kopalle et al. 1999). More specifically, we make the parameters of the within-channel promotion variables (μ_{1c}) a function of a constant (capturing the sensitivity to current within-channel promotions), a past promotion frequency variable in the own channel c ($Lpromo_{it,c}$; capturing the change in promotion sensitivity caused by within-channel delayed effects) and a past promotion frequency variable in the competing channel $\bar{c}$ ($Lpromo_{it,\bar{c}}$; capturing the change in promotion sensitivity caused by cross-channel delayed effects).[3]

(3) $$\mu_{1c} = \mu_{10,c} + \mu_{11,c} * Lpromo_{it,c} + \mu_{12,c} * Lpromo_{it,\bar{c}}.$$

[3] As will be explained in more detail in the Data section, the delayed effects are not weighted with household-specific preferences (they do remain household-specific as we only focus on visits to a channel where the household is in the opportunity to buy the category).

As explained in the conceptual framework section (H_2 and H_4 respectively), we expect that a high frequency of category promotions in channel c in the past reduces a household's category-specific sensitivity to subsequent promotions, in the own as well as the other channel. Hence, we expect that parameters capturing these within- and cross-channel delayed promotion effects are negative ($\mu_{11,c} < 0$ and $\mu_{12,c} < 0$).

We use a regression model to explain how much a household i buys in a category in a specific channel c during purchase occasion t, conditional upon a purchase decision ($b_{it,c} = 1$). We operationalize the category purchase quantity variable as the logarithm of the total quantity (in standardized units: milliliter for milk, gram for cereals) household i bought in channel c on purchase occasion t. The use of the logarithm ensures that the distribution of the continuous dependent variable is closer to normal (e.g., Fox et al. 2004; van Heerde et al. 2008). We define all the explanatory variables in equation (4) and (5) in the same way as before and have similar expectations regarding the parameters.

(4) $\ln(PQ^{*}_{it,c}) = \left(\beta_0 + \beta_1 * onvst_{it} + \beta_2 * \log(CR_i) + \beta_3 * \mathrm{MCINV}_{it} + \beta_4 * \log(INV_{it}) + \beta_{5c} * loyal_{it,c}\right) + \left(\delta_{1c} * promo_{it,c} + \delta_{2c} * promo_{it,\bar{c}}\right),$

(5) $\delta_{1c} = \delta_{10,c} + \delta_{11,c} * Lpromo_{it,c} + \delta_{12,c} * Lpromo_{it,\bar{c}}.$

To account for household differences in within- and cross-channel immediate and delayed promotion effects, the purchase incidence and quantity models are estimated using a latent class analysis approach. To keep the model tractable, and given our focus on promotion effects, we allow the parameters of the promotion effects to differ across consumer segments, while we keep the parameters of the control variables (i.e., online visit, consumption rate, inventory level, and loyalty) constant over different classes. In order to investigate if and how households may differ in their promotional reactions, we use a concomitant variable finitemixture model and formulate the latent segment membership as a function of household characteristics (see Gupta and Chintagunta 1994). More particularly, since we expect that promotional reactions may differ according to the degree of multi-channel shopping and category-specific chain loyalty (cf. conceptual framework; H_5), we use a multi-channel dummy variable ($MCShopper_i$) and the share of category purchases at the focal chain ($CatShare_i$) as concomitant variables to model the segment membership probabilities. Similar to the formulation used by Gupta and Chintagunta (1994), we specify the segment membership probability p_{ig} as:

(6) $$p_{ig} = \frac{\exp(\lambda_{0g} + \lambda_{1g} * MCShopper_i + \lambda_{2g} CatShare_i)}{1 + \sum_{m=1}^{G-1} \exp(\lambda_{0m} + \lambda_{1m} * MCShopper_i + \lambda_{2m} CatShare_i)}.$$

The log-likelihood function for the entire sample is given by:

(7) $$LL = \sum_{i=1}^{I} log\left(\sum_{g=1}^{G} p_{ig} \prod_{t=1}^{T_i} L_{it|g}\right),$$

where p_{ig} is household i's probability of belonging to segment g (g = 1, … G), T_i is the number of purchase occasions during which household i made a visit to the chain, and I is the number of households in the data. $L_{it|g}$ is household i's simultaneous likelihood for purchase incidence and quantity decisions on purchase occasion t (van Heerde and Neslin 2008), and is conditional upon i belonging to segment g:

(8) $$LL_{it|g} = y_{it,c} * \ln(P_g(b_{it,c} = 1)) + (1 - y_{it,c}) * \ln\left(1 - P_g(b_{it,c} = 1)\right) + Z_{it,c} *$$

$$P_g(PQ_{it,c} = PQ_{it,c}^* | b_{ict=1})$$

with $y_{it,c}$ as the category purchase indicator, equal to 1 if household i purchased the category in channel c on purchase occasion t, 0 otherwise; and $Z_{it,c}$ as the purchase quantity indicator, equal to 1 if household i purchased $PQ_{it,c}^*$ units in channel c on purchase occasion t – given purchase incidence, 0 otherwise.

DATA

We have data from a representative UK household panel from Kantar Worldpanel obtained from AiMark for the period starting July 2006 till December 2007. The UK online grocery market is, from all major online grocery markets, the most developed one (A.T. Kearney 2012): 74% of UK's population used the online channel for household grocery shopping activity in 2012 (Nielsen 2012). Our data cover 78 weeks of household (online and offline) grocery purchases at Tesco, the market leader in the grocery sector in the UK both for the online as well offline channel. Data of the first 26 weeks are used to initialize household-specific control variables and data of the next 52 weeks are used for model estimation. In addition, we have data of grocery purchases at other chains during the same period. These data will be used to (more) correctly operationalize the consumption rate, the inventory level, and the category-specific chain loyalty.

We estimate the category purchase decision models for two frequently purchased categories, milk and cereals. We include all households that made at least one store visit at the Tesco chain in the estimation period (irrespective of the channel, hence we include both single- as well as multi-channel shoppers) and that are regular users of the category (i.e., who have consumption rates equal to or larger than 25% of the consumption rate distribution across households). There are 9251 households (2175 multi-channel and 7076 single-channel offline shopper) for the milk category, and 7836 households (2034 multi-channel and 5802 single-channel offline shopper) for the cereals category.[4]

Table 2 provides some descriptives per category, divided between purchase behavior descriptives (Panel A) and marketing mix descriptives (Panel B). Panel A shows that, for multi-

[4] Our dataset does not include single-channel online shoppers, which is indicative of the fact that the big majority of online shoppers keeps on buying via the offline channel.

channel shoppers, category purchase frequency is higher offline, but the % of visits with a purchase and the quantity per shopping trip are substantially higher online. This confirms the finding of previous research that major trips are more likely to be made in the online channel, while fill-in trips are most likely to happen in the offline channel (e.g., Chintagunta et al. 2012). Comparing the (offline) purchases of multi- and single-channel shoppers, we find that multi-channel shoppers visit the offline store less frequently than single-channel shoppers and tend to buy larger quantities per shopping trip. This finding is in line with previous observations that especially time-constrained shoppers are more likely to take advantage of online shopping convenience benefits such as lower transaction costs and 24h availability from any place to order purchases (Degeratu et al. 2000; Perkins 2014).

<Insert Table 2 about here>

In terms of marketing mix variables (Panel B), it is interesting to note that the online assortment is a subset of the offline assortment and that it is substantially smaller for both categories. The average price (in standardized units) is, for both categories, lower in the online channel, but – taking only those SKUs into consideration that are offered in both channels – we find a price premium for the online channel in the milk category and a price premium for the offline channel in the cereals category. Still, for both categories, the price premium amount is quite small. Lastly, we find that, for both categories, the offline channel outperforms the online channel in terms of the average number of SKUs in promotion (10.17 offline vs. 2.56 online for milk, 25.12 offline vs. 5.12 online for cereals; which is in line with the difference in assortment size), but promotional advantages tend to be larger in the online than offline channel (13.84% offline vs. 17.5% online for milk, 22.38% offline vs. 27.64% online for cereals). Also here, we find, for both categories, an overlap with simultaneous promotions in about 1 out of 2 cases for the online channel (about 50% of the promoted SKUs in a particular week in the online channel are also in promotion in the offline channel). This suggests that there is a common base for the promotional calendar of the online and offline channel (because manufacturers for instance have a say on how promotions are scheduled across all retailers), but both channels do keep a significant amount of independence and own responsibility for day-to-day operations like promotion plans.

Table 1 shows the variable operationalization. We highlight some key features of the variable operationalization here and describe the details in Table 1. We use the initialization period of 26 weeks to compute the consumption rate and to provide a starting value for the inventory level. Consumption rate is defined as the weekly average category purchase quantity of household i across channels and chains in the initialization period. The inventory level is updated using household i's inventory and purchase quantity from the previous week (at the Tesco chain and at the other chains) and the weekly consumption rate. The channel loyalty variable ($loyal_{it,c}$) is a weighted average of past loyalty and the households' previous channel choice for the category at the Tesco chain (1 if channel c was selected on the previous purchase occasion and 0 otherwise). The concomitant variables are operationalized as a multi-channel dummy variable which captures whether household i is a single-channel (0) or multi-channel (1) shopper, and as the share of category purchases at Tesco v-a-v the other chains which captures category-specific chain loyalty.[5]

To construct the promotion variables, we first determine the price discount depth variable which equals the price discount (in %) when SKU n was on promotion in a week, 0 otherwise. To identify promotions, we use a procedure similar to prior research based on price deviations

[5] This time-invariant variable indicates whether households are more or less category loyal at the focal chain. It is not to be confused with the time-specific channel loyalty variable ($loyal_{it,c}$) which traces a household's preference for a specific channel at the focal chain during the course of time.

from the average price level (see Nijs et al. 2001; Geyskens et al. 2010). More specifically, we identify promotions as SKUs where the unit price in a particular week is at least one standard deviation below its average price level.[6] Next, we calculate the price discount for those SKUs that are on promotion as the difference between the average price for SKU n minus the unit price for SKU n in a particular week divided by the average price for SKU n. In order to make these promotion variables household-specific, we (i) focus on visits to a channel where the household is in the opportunity to buy the category and (ii) use SKU spending shares in each household's long-term shopping basket (across all chains) in the entire time period as weights, which reflects household-specific SKU preferences. Promotional variables are thus larger when (i) more SKUs are promoted and/or (ii) larger price discounts are given and/or (iii) promotions concern SKUs that are preferred (frequently bought in the past) by households.

We operationalize the past promotion frequency variables ($Lpromo_{it,c}$, $Lpromo_{it,\bar{c}}$) as a weighted sum of category promotions in a specific channel during the past 26 weeks, given that household i visited that channel (and thus was exposed to the promotions in that channel). Because we want to capture the overall effect of perceived (past) and expected (future) promotion opportunities in the category (see e.g., Foekens et al. 1999; Kopalle et al. 1999), we take all SKU promotions in the category into account (hence, no weighting with household-specific preferences). In line with previous research, we use a decay factor as 'weight' to control for recency and frequency effects. The resulting past promotion frequency variable is larger

[6] We used the entire estimation period to determine the average price and its standard deviation. For milk, there was a significant price increase in week 62 (week 36 of the estimation period) both in the online and offline channel. Therefore, we calculated an average price for the period before the price increase and one for the period after the price increase. To verify our classification of (no) promotion SKUs/weeks, we conducted a number of robustness checks where we used different operationalizations of the average price level (e.g., based on a moving window) and different cut-offs (e.g., two standard deviations). These results show that our classification is robust.

when a household was more frequently and recently exposed to category promotions within the time window.

(9) $Lpromo_{it,c} = \sum_{s=1}^{26} \lambda^{s} * promo_{it-s,c}$

EMPIRICAL RESULTS

We estimated the above-stipulated model with a varying number of latent classes. Although additional segments provide a further improvement in goodness-of-fit for both models, there is a clear elbow (Figure 2) in the information criteria graph at three segments for both milk and cereals, with additional segments providing only a minor improvement in fit and coming at the cost of lower face validity of the results. Table 3 and 4 report the estimation results for the homogeneous and the three-segment model, for respectively milk and cereals. The estimation results for incidence are presented in Panel A and those for quantity in Panel B.

<insert Figure 2 here>

<Insert Table 3 and 4 about here>

Estimation results: homogeneous model

For each category, we obtain – for both purchase incidence and quantity – significant and expected positive effects for consumption rate (α_2 = .325 and β_2 = .605 for milk; α_2 = .428 and β_2 = .301 for cereals), significant and expected negative effects for the mean-centered inventory variable (α_3 = -.101 and β_3 = -.055 for milk; α_3 = -.207 and β_3 = -.094 for cereals), and significant and expected positive effects for log inventory (α_4 = .027 and β_4 = .032 for milk; α_4 = .035 and β_4 = .020 for cereals). We also confirm that the online correction parameter has, as expected, a positive effect on both purchase incidence and quantity decisions (α_1 = .926 and β_1 = .279 for milk; α_1 = .904 and β_1 = .128 for cereals), reflecting the tendency to buy larger baskets online.

The channel-specific category loyalty variables have an expected positive effect on purchase incidence decisions ($\alpha_{5,1}$ = 1.114 and $\beta_{5,2}$ = 1.271 for milk; $\alpha_{5,1}$ = .509 and $\beta_{5,2}$ = .780 for cereals).

The within-channel immediate promotion effects are significant and have the expected positive sign ($\mu_{10,1} / \delta_{10,1} > 0$ and $\mu_{10,2} / \delta_{10,2} > 0$), which confirms H_1. Also the cross-channel immediate effects are significant and as expected in H_3 negative ($\mu_{2,1} / \delta_{2,1} < 0$ and $\mu_{2,2} / \delta_{2,2} < 0$), with the exception of the cross-channel effect of offline promotions on online purchase quantity for cereals which is not significant. For the within- and cross-channel delayed promotion effects, we observe for the majority of cases significant negative effects (as expected in H_2 and H_4). Yet, for both categories, there are a few significant (unexpected) positive effects but the negative effects clearly outnumber the positive effects, especially for the cereals category (5 / 7 negative and significant within- and cross-channel delayed coefficients and 3 / 1 positive coefficients for milk / cereals).[7]

Estimation results: heterogeneous model

Like for the homogeneous model, we find that all the coefficients of the control variables are significant and have the expected sign. Given that we are interested in exploring if and how household segments react differently to promotional effects (see H_5), we zoom in on segment differences. Overall, for each category, the three segments exhibit some distinctive patterns in consumers' responses to promotions, which are in line with our expectations.

[7] A possible explanation for positive delayed promotion effects is that a higher promotion frequency could make consumers more price-conscious, and thereby increase their price sensitivity (Kopalle et al. 1999; Mela et al.1998). When delayed promotion effects are included into the model as main effects (instead of indirect effects on promotion sensitivity), the number of positive significant within- and cross-channel delayed effects was even higher (see robustness checks). A possible explanation for this is that many retailers offer promotions over a longer period of time, e.g. 4 weeks instead of 1 week (especially when promotions are featured in the store flyer). When the inventory variable adequately captures post-promotion dip effects, the lagged promotion variables may take away some of the main (current) promotion effect.

For both categories, we obtain segments with a larger share of multi-channel, loyal Tesco shoppers in the category (segment 1 and 3 for milk, and segment 1 and 2 for cereals). In line with our expectations, we find clear evidence of both negative cross-channel immediate and delayed promotion effects for these segments, with a notable higher number of significant negative cross-channel effects for these segments (4 out of 8 for both segment 1 and 3 for milk, 4 out of 8 for segment 1 for cereals, and 2 out of 8 for segment 2 for cereals). Hence, as expected in $H_{5a\text{-}d}$, consumers that use both channels of one single chain are more likely to experience negative cross-channel effects, both for the current purchase decisions as well as on their sensitivity towards promotional actions of that chain. While the cross-channel promotion effects are clearly more pronounced for these segments (compared to segment 2 for milk and segment 3 for cereals), these two segments differ among each other with respect to their general promotional responsiveness. Customers of segment 1 for milk and segment 1 for cereals are much more sensitive to online as well as offline promotions (significant positive main effects in 3 and 4 out of 4 cases for milk and cereals respectively).

For both categories, there is also one segment with a smaller percentage of multi-channel and less loyal Tesco shoppers in the category (segment 2 for milk and segment 3 for cereals, who on average, respectively buy only 40% and 57% of category purchases at Tesco).[8] As expected in $H_{5a\text{-}d}$, these segments display almost no significant cross-channel effects (no significant effects for segment 2 for milk, and 1 significant effect for segment 1 for cereals). As these customers tend to spread their category purchases across Tesco and other chains, promotion pre-emption effects can be distributed over the focal chain (Tesco) and other visited chains, leading to substantially lower or insignificant cross-channel promotion effects for Tesco.

[8] Although the multi-channel dummy variable is not significant in the three-segment solution for cereals, posterior chi-square tests confirm that for both categories the multi-channel share significantly differs across the three segments (milk: $\chi(2)=134.325$; $p<.001$; $\chi(2)=13.896$; $p=.001$).

Finally, it is interesting to note that – in line with the results of the homogeneous model and for both categories – cross-channel delayed effects on promotion sensitivity are much weaker compared to within-channel delayed effects. For the three-segment model, we observe only 2 significant negative cross-channel delayed effects vs. 5 significant negative within-channel delayed effects for milk, and 2 significant negative cross-channel delayed effects vs. 6 significant negative within-channel delayed effects for cereals.

Robustness checks

We conducted several robustness checks to verify the validity and specification of our model variables and the consistency of our findings. First, we tested different specifications for the baseline purchase tendency in the absence of promotions. Instead of the consumption rate and inventory variable combination used to capture the effect of category needs and dynamic promotion effects (purchase acceleration and stock-piling effects), we tested a model with an average spending variable (computed over the initialization period) and a mean-centered lagged spending variable, and one with the 'traditional' positive consumption rate and negative inventory effect (cf. Bucklin and Lattin 1991; Chintagunta 1993). Although results were very similar, we found that our model specification outperformed the alternative specification.

Second, to assess whether additional post-promotion dips exist over and above what is explained by the (rational) inventory effects, we ran models where we included – next to the inventory variables – short-term lagged promotion variables (based on the previous purchase occasion) and longer-term delayed promotion variables (over a longer time period, taking frequency and recency effects into account). The face validity of the results of these alternative model specifications significantly decreased, as we obtained a high number of significant *positive* lagged promotion coefficients.

In addition, instead of using the price discount depth variable as stipulated before, we tested alternative operationalizations for the promotion variable including the number of SKUs in promotion and the absolute price discount amount. While we obtained very similar results with the ‘number of promotions’ specification; the absolute price discount amount operationalization clearly provided inferior estimation results. We further relaxed the restriction that promotion variables only come into play when consumers visit the other channel, by estimating a model where cross-channel effects are taken into consideration irrespective of whether the channel was visited in the previous weeks. Results point out that this model fit is significantly lower. To assess whether negative cross-channel effects are still significant when accounting for the fact that they only occur when a consumer visited both the online and offline channel in the same week, we also estimated a model including a dummy variable that corrected for the visit to both channels. We still obtained negative and significant cross-channel effects in some segments, but the face validity of other parameter estimates was substantially better for our final model specification. We also checked the sensitivity of the weight (.75) used to capture fading effects for constructing the delayed promotion variables (see Equation 9 and Table 1), but obtained similar results for decay factors in the .5 to .9 range.

Finally, we examined the effect of sample selection by estimating our model, using a larger sample (where we place no cut-off for consumption rates and thus also include very light users of the category) as well as a smaller sample (where we focus on multi-channel shoppers only). Estimation results on the larger sample provided substantially inferior results, and we therefore decided to retain regular users of the category only. Estimation results for the smaller sample of multi-channel shoppers only were very similar. However, given that consumers who shop primarily in one channel are a substantial portion of the population in most markets (especially for groceries and the offline channel), and retailers care about overall sales and overall promotion lift, we feel it is justified to include single-channel shoppers in our model estimation.

DISCUSSION AND CONCLUSION

The major objective of this research was to examine cross-competitive effects of category promotions in a multi-channel context and the way they may affect consumers' category purchase decisions. Based on the traditional sales promotions literature, we defined three areas that needed to be investigated in order to obtain a better insight into these effects: (i) the promotions' immediate effect on category purchase decisions in the other channel, (ii) the promotions' delayed effect on future promotion sensitivity in the other channel, and (iii) consumer differences in these cross-channel promotion effects and their underlying factors.

Cross-channel immediate effects

Our results replicate previous findings that sales promotions can have an immediate positive effect on category purchase decisions, both in the offline and online channel. We are, however, the first to provide evidence that promotions can also have immediate *negative* effects on purchase decisions in the other channel. By pre-empting category purchases in the other channel (reduced purchase incidence probability and/or reduced quantity in the other channel), channel differences in promotion attractiveness can, within the same chain, lead to a shift in category sales from one channel to the other. These shifts may depend on the extent to which promotions increase the relative attractiveness of a category, which is a function of the number of items on promotion, and/or the price discount depth and/or consumer preferences for promoted SKUs.

Cross-channel delayed effects

Consistent with previous research, we find that a high frequency of promotions in the offline channel reduces the consumers' promotion sensitivity on subsequent visits to the offline channel (Foekens et al. 1999; Kalyanaram and Winer 1995; Kopalle et al. 1999). Interestingly, while online stores are typically visited less frequently (Chu et al. 2010; see Table 2), we provide evidence for a similar within-channel delayed promotion effect in the online channel, showing that frequent exposure to online promotions can also reduce consumers' sensitivity to future online promotions. More importantly, a high promotion frequency in the past in one channel does not only affect future promotion sensitivity in the same channel, but it can also influence promotion sensitivity in the other channel. Hence, they can have additional, longer-term negative effects on consumer promotion sensitivity but only to a limited extent as our results point out that within-channel delayed effects clearly dominate cross-channel delayed effects.

Household differences

Prior research has indicated that promotional responses may differ across households (van Heerde and Neslin 2008). In this research, we confirm that cross-channel immediate and delayed effects are more pronounced for some households than for others. More particularly, we find that multi-channel shoppers who visit the offline and online store of the same chain, and category loyal customers of the chain who tend to concentrate purchases of a particular category at one chain are much more likely to shift category purchases across channels rather than chains (resulting in stronger cross-channel immediate effects), and tend to be more sensitive to the promotion frequency in the focal chain (resulting in stronger cross-channel delayed effects). In contrast, cross-channel effects have a much weaker effect for segments who visit both channels, but also more chains, i.e., who spend a lower share of category purchases at Tesco. These consumers do not only have the opportunity to shift purchases from one channel to the other, but also from competitive stores to the focal chain.

MANAGERIAL IMPLICATIONS

Given the high growth rate of multi-channel retailing in recent years (Neslin et al. 2006; Neslin and Shankar 2009, Shankar et al. 2011), it is getting more and more important for marketing managers to better understand how to manage promotions in the complex multi-channel shopping environment. Our research provides new and interesting insights that can help multi-channel retailers in optimizing their multi-channel strategy.

First, our findings demonstrate that category sales promotions are an effective instrument to stimulate primary demand (i.e., category purchase incidence and quantity), both in the offline and online channel. We find, in both examined categories for all segments, significant positive immediate promotion effects at the incidence and/or quantity level. A second important insight is that cross-channel promotion effects are substantial and negative, and should be taken into account to correctly assess the promotions’ effectiveness and to define optimal promotion plans. The findings on cross-channel immediate promotion effects indicate that positive within-channel promotion effects can be counteracted by the negative effect they produce in the other channel. Hence, while channel differences in promotion attractiveness can be used by multi-channel retailers to stimulate sales within one channel (e.g., because of differences in profit margin and/or consumers' price sensitivity), the ultimate outcome on overall category performance remains uncertain. When differentiated promotions merely lead to shifts of purchases from one channel to the other over time, the advantages of offering channel-specific promotions may not weigh up against the risks of increased promotion exposure (cf. cross-channel delayed promotion effects).

Yet, these cross-channel delayed effects do not really seem to reinforce the decrease in promotion sensitivity in response to higher promotion exposure in the past. While we find that – in line with previous research – frequent promotions within a channel can reduce the consumers' future promotion sensitivity within the same channel, a high frequency of promotions in one channel only has a very limited effect on the sensitivity to future promotions in the other channel. Hence, the greater variety of sales promotions that multi-channel shoppers are exposed to does not seem to entail a substantial risk of aggravating the reduction in promotion sensitivity following a high promotion frequency in the past.

Last but not least, cross-channel immediate and delayed promotion effects substantially differ across households. These effects are much more pronounced for multi-channel shoppers who visit the offline and online store of the same chain, and category loyal customers of the chain who tend to concentrate purchases of a particular category at one chain. Managers, therefore, need to be wary of these negative cross-channel effects for these consumer segments. Especially for chains with a large percentage of loyal customers, such as Tesco, making use of channel differences in promotion sensitivity to improve category and store performance (Wolk and Ebling 2010) may be difficult to realize, as differentiated promotion strategies can mainly lead to cross-channel cannibalization and 'extra subsidization' of loyal customers of the chain.

LIMITATIONS AND FUTURE RESEARCH

While our research results provide interesting new insights into cross-channel effects of promotions in a multi-channel context, it also has a number of limitations and provides indications for further research in several interesting areas. First, we concentrate on temporary price discount promotions and do not distinguish between promotions that are initiated by either the manufacturer or retailer, nor do we have data to differentiate among the sales promotion forms (e.g., price vs. no-price promotions) and ways of communication (e.g., store flyer vs. in-store promotions). We do acknowledge that it would be extremely interesting to further investigate different promotion types and to assess the importance of the type and communication vehicle of promotion advantages. Second, we only investigated cross-channel promotion effects for two categories. Analyzing a larger set of categories – that differ on characteristics such as perceived online purchase risk, shopping convenience, variety seeking tendency, etc. – and explicitly linking cross-channel effects to category characteristics could help to derive more specific guidelines for multi-channel promotion planning.[9] What is more, we only focus on an online grocery shopping context. Replicating the study in other multi-channel retail settings would be an interesting area for further research. Also, our research focuses on cross-channel promotion effects at the category level. While category level effects are the most relevant from a retailer point of view, it could also be interesting to investigate cross-channel effects at the brand level, as manufacturers may face a similar multi-channel promotion planning problem when selling their brand through a multi-channel retailer. Likewise, it would be equally

[9] In a preliminary analysis, where we used a more restricted data set (with, for instance, no information on promotion depth, multi-channel shoppers only), we examined cross-channel promotions effects over a larger set of 6 categories. We essentially arrived at the same major conclusions regarding cross-channel promotions effects, and found some indications of cross-category differences.

interesting to further investigate the impact of cross-promotions on traffic building/channel visit and on cross-category purchase behavior. Lastly, our research focuses on an analysis of cross-channel promotion effectiveness in a multi-channel single-chain context. Incorporating chain and channel choice decision into the model estimations would greatly complicate the analysis, and could lead to interesting but less focal additional insights. Nevertheless, we consider it a promising avenue for additional research to investigate cross-channel promotion effectiveness in a multi-channel multi-chain context, where chain and channel choice decisions are explicitly modeled and where activities of competitive chains could be taken into account. Such an analysis would provide a more complete picture of promotion effects and consumer shopping behavior in the extremely complex multi-channel multi-chain shopping environment. Likewise, it would be interesting to investigate in more detail – in an experimental context, for instance, where focal variables can be controlled better – how promotion programs (more or less differentiation) influence category and store performance, and how this differs across chains.

Figure 1: Conceptual Framework

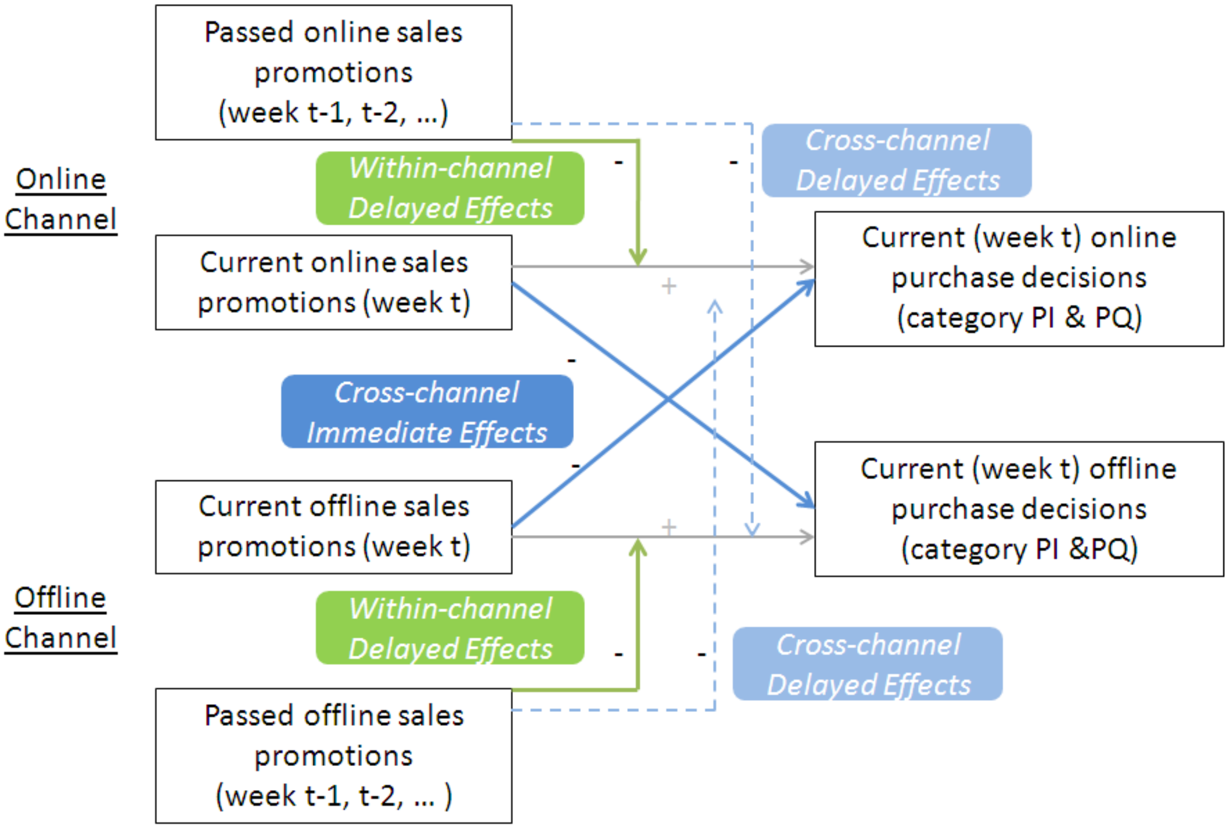
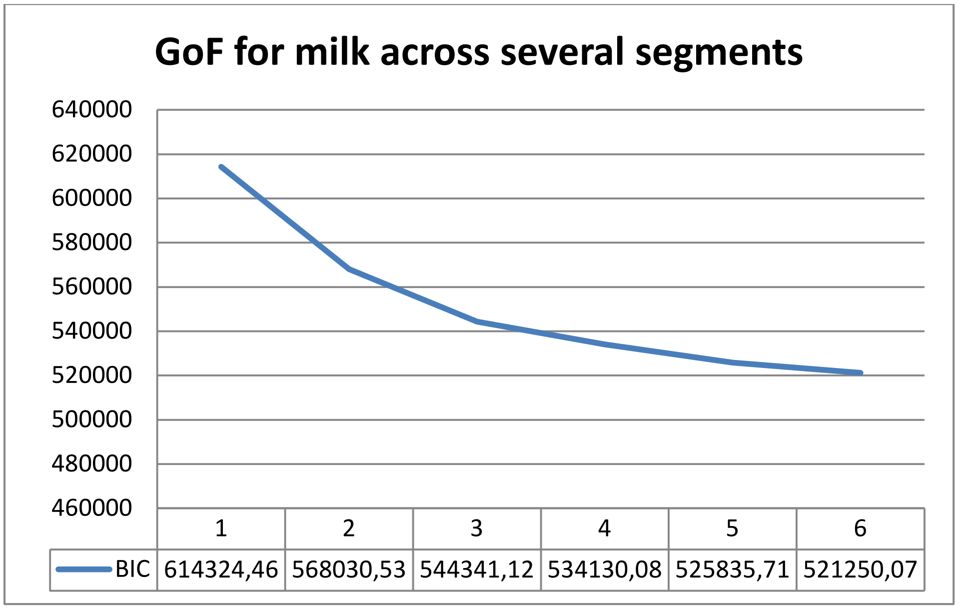


Figure 2: Model Goodness-of-Fit

Panel A: Milk



Panel B: Cereals

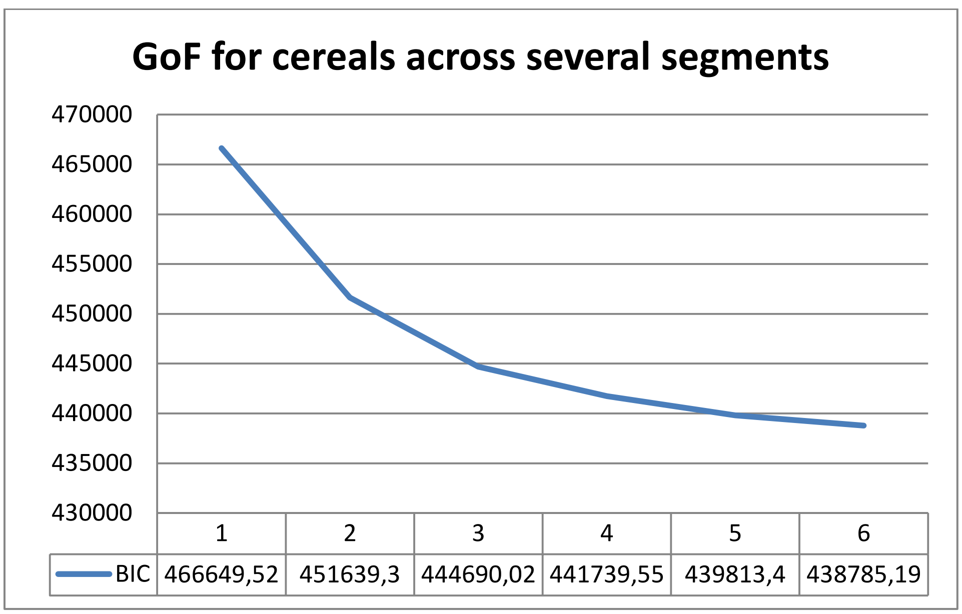


Table 1: Variable operationalization

Notation	Name	Description	Specification
$b_{it,c}$	Category purchase incidence for household i in channel c on t	Indicator variable, equal to 1 if household i makes a category purchase in channel c on purchase occasion t (i.e., week with a shopping trip), 0 else.	
$lnPQ_{it,c}$	Logarithm of category quantity for household i in channel c on t	Logarithm of total quantity that was bought in a category (in standardized units: milliliter-milk, gram-cereals) for household i in channel c on purchase occasion t.	
$Onvst_{it}$	Visit to the online channel for household i on purchase occasion t	Indicator variable, equal to 1 if household i visits the online channel on purchase occasion t, 0 elsewhere.	
$Both\_vst_{it}$	Visit to both channels for household i on purchase occasion t	Indicator variable, equal to 1 if household i visits both channels on purchase occasion t, 0 elsewhere.	
CR_i	Weekly consumption rate for household i	Overall total quantity of the category bought by household i in all channels and chains in the initialization period (PQ_{is}; s=1,…,26; s=week indicator) divided by number of weeks in initialization period (26).	$CR_i = \sum_{s=1}^{26} PQ_{is}/26$
INV_{it}	Inventory rate for household i on purchase occasion t	The inventory in the previous week ($INV_{i,s-1}$), plus the amount bought in the previous week across all chains ($PQ_{i,s-1}$) minus the weekly consumption rate (CR_i). If this inventory level is smaller than 0, we use 0. The inventory level at the starting point of the initialization period (INV_{i0}) is set equal to 0.	$INV_{it} = \max[0, (INV_{i,s-1} + PQ_{i,s-1} - CR_i)]$
INV_{it}	Mean-centered inventory rate for household i on purchase occasion t	Mean-centered version of the inventory rate, using the average inventory for household i (AVG_INV_i) for mean-centering.	$MCINV_{it} = \frac{INV_{it}}{AVG\_INV_i}$
$loyal_{it,c}$	Loyalty variable for household i in channel c on purchase occasion t	Weighted average of past loyalty for the category in channel c at the focal chain ($loyal_{i,t-1,c}$) and channel choice at the focal chain on the last purchase occasion ($b_{i,t-1,c}$) for household i, with weight θ = .7 to capture fading effects.	$loyal_{it,c} = \theta * loyal_{i,t-1,c} + (1-\theta) * b_{i,t-1,c}$
$WPctDisct_{is,c}$	Average percentage price reduction for household i in channel c in week s	The average % of price discount ($PctDisct_{nsc}$) of a category across all SKUs (n=1, … N) in channel c in week s, weighted by spending shares for SKU n in each household i's long-term shopping basket in the focal chain (w_{in}). Promotions are determined based on price deviations from the average price level (equal to 1 if unit price of SKU n in week s < (average price of SKU n – 1 standard deviation)). Next, price discount percentage is calculated as the difference between average price of SKU n minus unit price of SKU n in week s, divided by average price of SKU n.	$WPctDisct_{is,c} = \sum_{n=1}^{N} w_{in} * PctDisct_{ns,c}$
$Promo_{it,c}$	Current sales promotions for household i in channel c on purchase occasion t	Weighted percentage price reduction for household i in channel c, *given* that household i visits the channel in purchase occasion t.	$Promo_{it,c} = WPctDisc_{it,c} * Vst_{it,c}$
$Promo_{it,\bar{c}}$	Current sales promotions for household i in channel $\bar{c}$ on purchase occasion t	Weighted percentage price reduction for household i in channel $\bar{c}$, given that household i visits both channels in purchase occasion t.	$Promo_{it,\bar{c}} = WPctDisc_{it,c} * Vst_{it,c} * both\_vst_{it}$
$Lpromo_{it,c}$	Past promotion frequency for household i in channel c on purchase occasion t	Weighted sum of previous promoted items of the category (number of promoted items, $Nrpromo_{i,t-s,c}$) on purchase occasion t, given the visits of household i in channel c in past 26 weeks (s=1, …, 26), with weight λ = .75 to capture fading effects.	$Lpromo_{it,c} = \sum_{s=1}^{26} \lambda^s * Nrpromo_{i,t-s,c}$
$MCShopper_i$	Multi-channel dummy variable for household i	Indicator variable, equal to 1 if household i visits the online and offline channel (multi-channel shopper), 0 elsewhere (single-channel shopper).	
$CatShare_i$	Share of category purchases at the focal chain for household i	Overall total quantity of the category bought by household i in the estimation period in all channels at the focal chain Tesco (PQ_{i_Tesco}) v-a-v the overall total quantity of the category bought by household i in all channels at all chains (PQ_{i_All}).	$CatShare_i = \frac{PQ_{i\_Tesco}}{PQ_{i\_All}}$

Table 2: Descriptive Statistics[†]

Panel A: Purchase behavior descriptives

		Milk			Cereals		
		Total	Single-channel (offline)	Multi-channel	Total	Single-channel (offline)	Multi-channel
Number of shoppers[a]		9251	7076 (76.49%)	2175 (23.51%)	7836	5802 (74.04%)	2034 (25.96%)
Number of observations[b]	Off	251807	194457	57350 (74.3%)	233288	167861	65427 (77.4%)
	On		N/R	13028 (16.9%)		N/R	12939 (15.3%)
	Both		N/R	6750 (8.8%)		N/R	6137 (7.3%)
Average purchase frequency (# purchases/ week)	Off	.70 (min:.04) (max:1) (s.e.:.24)	.72 (min:.08) (max:1) (s.e.:.23)	.65 (min:.04) (max:1) (s.e.:.27)	.70 (min:.02) (max:1) (s.e.:.25)	.73 (min:0) (max:1) (s.e.:.23)	.62 (min:.02) (max:1) (s.e.:.29)
	On		N/R	.14 (min:.02) (max:1) (s.e.:.20)		N/R	.15 (min:.02) (max:.96) (s.e.:.21)
Shopping trip quantity (in standardized units/trip)[c]	Off	2.92 (min:0.02) (max:21.91) (s.e.:2.21)	2.84 (min:0.02) (max:21.52) (s.e.:2.17)	3.14 (min:0) (max:21.91) (s.e.:2.29)	4.17 (min:0) (max:61.42) (s.e.:3.43)	4.13 (min:0) (max:61.42) (s.e.:3.30)	4.26 (min:0) (max:39.10) (s.e.:3.75)
	On		N/R	3.11 (min:0) (max:33.45) (s.e.:3.24)		N/R	5.77 (min:0) (max:100) (s.e.:7.4)
Sales (in £/year)[a]	Off	396801	298212 (75.0%)	98589 (25.0%)	245181	184003 (75.0%)	61178 (25.0%)
	On		N/R	36985		N/R	35578

[†] N/R = not relevant.
[a] % of total in the category, across shopper segment.
[b] % of total in the shopper segment per category.
[c] expressed in standardized units: liters for milk, kilograms for cereals.

Panel B: Marketing mix descriptives

	Milk		Cereals	
	Offline	Online	Offline	Online
# SKUs in the assortment	79	23	187	42
% of overlap with assortment of other channel	27.85%	95.65%	21.93%	97.62%
Average price (in £)[a]	Mean: .75 (s.e.: .26)	Mean: .61 (s.e.: .13)	Mean: 3.38 (s.e.: 1.61)	Mean: 3.25 (s.e.: 1.56)
Price differential (for SKUs offered in both channels)[b]	Mean: .006 (s.e.: .060)		Mean: -.015 (s.e.: .504)	
# SKUs on promotion per week[c]	Mean: 10.17 (s.e.: 12.03) (min.: 0) (max: 36)	Mean: 2.56 (s.e.: 3.28) (min.: 0) (max: 11)	Mean: 25.12 (s.e.: 15.60) (min.: 1) (max: 64)	Mean: 5.15 (s.e.: 4.25) (min.: 0) (max: 20)
% depth of price discount[c]	Mean: .1384 (s.e.: .0476) (min.: .0385) (max: .3266)	Mean: .1750 (s.e.: .0774) (min.: .0147) (max: .4100)	Mean: .2238 (s.e.: .0514) (min.: .1643) (max: .5422)	Mean: .2764 (s.e.: .0825) (min.: .1220) (max: .4911)
% of overlap[d]	11.59%	46.21%	10.85%	52.81%

[a] expressed in standardized units: liters for milk, kilograms for cereals.
[b] price differential is computed as the difference in online unit price and offline unit price for those SKUs that are offered in both channels. For both categories, the online assortment is a subset of the offline assortment (with the exception of 1 SKU in the online channel for both categories).
[c] these variables are not weighted with household-specific preference shares.
[d] % of SKUs that are simultaneously promoted in both channels compared to overall number of promotions.

Table 3: Estimation Results Milk†

		Homog. model	3 segment model		
			Seg.1	Seg.2	Seg.3
Category Purchase Incidence Decision					
	Intercept Offline (α_0)	-.821**	-.415**	-1.216**	-.072**
	Intercept Online (α_1)	.926**		.505**	
	Log cons. rate (α_2)	.325**		.360**	
	Inventory, MC (α_3)	-.101**		-.099**	
	Log inventory (α_4)	.027**		.021**	
	Loyalty Online ($\alpha_{5,1}$)	1.114**		1.144**	
	Loyalty Offline ($\alpha_{5,2}$)	1.271**		.935**	
Within-channel	Online → Online ($\mu_{10,1}$)	2.509**	3.686**	2.495	-.215
Immediate	Offline → Offline ($\mu_{10,2}$)	.194**	.231	.649	-2.593**
Within-channel	Online → Online ($\mu_{11,1}$)	-.410**	-.590	.669	-.446
Delayed	Offline → Offline ($\mu_{11,2}$)	.163**	.017	.049	.219**
Cross-channel	Online → Offline ($\mu_{2,1}$)	-6.570**	-9.070**	-2.963	-9.524**
Immediate	Offline → Online ($\mu_{2,2}$)	-2.742**	-2.704	8.440**	-6.714**
Cross-channel	Online → Offline ($\mu_{12,1}$)	1.419**	.680	.523	.002
Delayed	Offline → Online ($\mu_{12,2}$)	-.064**	-.120	-.234	.004
Category Quantity Decision					
	Intercept Offline (β_0)	.614**	.960**	.179**	.475**
	Intercept Online (β_1)	.279**		.214**	
	Log cons. rate (β_2)	.605**		.618**	
	Inventory, MC (β_3)	-.055**		-.030**	
	Log inventory (β_4)	.032**		.018**	
Within-channel	Online → Online ($\delta_{10,1}$)	1.939**	1.649**	2.262*	-.275
Immediate	Offline → Offline ($\delta_{10,2}$)	2.781**	1.207**	2.649**	.860**
Within-channel	Online → Online ($\delta_{11,1}$)	-.402**	-.329**	-.618*	-.026
Delayed	Offline → Offline ($\delta_{11,1}$)	-.101**	-.073**	-.079**	-.031**
Cross-channel	Online → Offline ($\delta_{2,1}$)	-2.595**	-5.107**	.673	-1.653**
Immediate	Offline → Online ($\delta_{2,2}$)	-2.152**	-1.916**	.645	-.996
Cross-channel	Online → Offline ($\delta_{12,1}$)	.226**	.069	.290	.351
Delayed	Offline → Online ($\delta_{12,2}$)	-.151**	-.120***	.047	-.065*
	Variance	.305**		.232**	
Segment Membership					
Intercept			-2.602**	4.803**	-2.202**
Multi-channel			.186**	-.220**	.034**
Category share			3.852**	-7.386**	3.534**
Segment size			33.9%	29.1%	37.0%
% multi-channel shoppers			28%	15.7%	26%
Average category share			92%	40%	90%
Model fit (BIC)		614324.64		544341.12	

† ** Significant at 1% level. * Significant at 5% level.

Table 4: Estimation Results Cereals†

		Homog. model	3 segment model		
			Seg.1	Seg.2	Seg.3
Category Purchase Incidence Decision					
	Intercept Offline (α_0)	-.256**	.198**	.501**	-.411**
	Intercept Online (α_1)	.904**		.504**	
	Log cons. rate (α_2)	.428**		.414**	
	Inventory, MC (α_3)	-.207**		-.206**	
	Log inventory (α_4)	.035**		.023**	
	Loyalty Online ($\alpha_{5,1}$)	.509**		.631**	
	Loyalty Offline ($\alpha_{5,2}$)	.778**		.392**	
Within-channel	Online → Online ($\mu_{10,1}$)	2.892**	8.022**	-.718	1.273
Immediate	Offline → Offline ($\mu_{10,2}$)	1.342**	1.123**	1.185**	1.021**
Within-channel	Online → Online ($\mu_{11,1}$)	-4.869**	-14.245**	-1.480	-1.211
Delayed	Offline → Offline ($\mu_{11,2}$)	-2.024**	-3.355**	-2.028**	-.785
Cross-channel	Online → Offline ($\mu_{2,1}$)	-5.664**	-4.708**	-8.076**	-5.696**
Immediate	Offline → Online ($\mu_{2,2}$)	-1.380**	-1.196	-3.477**	.892
Cross-channel	Online → Offline ($\mu_{12,1}$)	4.430**	.328	.270	.240
Delayed	Offline → Online ($\mu_{12,2}$)	-3.386*	-17.450**	.469	3.252
Category Quantity Decision					
	Intercept Offline (β_0)	.235**	.521**	.067**	.106**
	Intercept Online (β_1)	.128**		.123**	
	Log cons. rate (β_2)	.301**		.309**	
	Inventory, MC (β_3)	-.094**		-.081**	
	Log inventory (β_4)	.020**		.013**	
Within-channel	Online → Online ($\delta_{10,1}$)	1.773**	2.353**	.154	.329
Immediate	Offline → Offline ($\delta_{10,2}$)	1.640**	2.005**	.735**	.228
Within-channel	Online → Online ($\delta_{11,1}$)	-3.798**	-8.267**	-1.858	-2.396
Delayed	Offline → Offline ($\delta_{11,2}$)	-5.699**	-4.886**	-1.585**	.064
Cross-channel	Online → Offline ($\delta_{2,1}$)	-1.655**	-3.771**	-.271	-2.164
Immediate	Offline → Online ($\delta_{2,2}$)	-.302	1.101	-.404	-.750
Cross-channel	Online → Offline ($\delta_{12,1}$)	-2.790**	-6.460**	.580	-2.968
Delayed	Offline → Online ($\delta_{12,2}$)	-2.358**	-2.107	-1.090	1.551
	Variance	.337**		.300**	
Segment Membership					
Intercept			-1.420**	-2.717**	4.1371
Multi-channel			.067	-.050	-.017
Category share			1.882**	3.264**	-5.146**
Segment size			32.4%	29.9%	37.8%
% multi-channel shoppers			28%	26%	24%
Average category share			89.6%	92.0%	57.0%
Model fit (BIC)		466649.52		444690.02	

† ** Significant at 1% level. * Significant at 5% level.

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